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Development of machine vision and laser radar based autonomous vehicle guidance systems for citrus grove navigation

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Abstract

Current production navigation systems for agricultural vehicles rely on GPS as the primary sensor for steering control. In citrus groves, where the tree canopy frequently blocks the satellite signals to the GPS receiver, an alternative method is required. This paper discusses the development of an autonomous guidance system for use in a citrus grove. The vehicle used for this study was a common tractor. Machine vision and laser radar (ladar) were individually used for guidance and a rotary encoder was used to provide feedback on the steering angle. A PID controller was developed to minimize the path error. The vehicle's guidance accuracy was tested in flexible test paths constructed of common hay bales. Path tracking performance was observed. The guidance system guided the tractor automatically through straight and curved paths. An average error of 2.8 cm using machine vision guidance and an average error of 2.5 cm using ladar guidance was observed, when the vehicle was tested in a curved path at a speed of 3.1 m/s. The guidance system successfully guided the vehicle in a citrus grove alleyway.

Keywords: Automatic guidance; Machine vision; Laser sensor; Control

1. Introduction

Florida supplies over 80% of United States' supply of citrus. Over the years, the labor supply for citrus harvesting has declined. Immigration restrictions have limited the movement of migrant workers. The citrus industry is also facing increased competition from overseas markets. As a result, the need for automation is being felt in the citrus industry. An important part of the automation process is vehicle guidance. Sample autonomous vehicle applications may include harvesting, disease or nutrient deficiency monitoring, mowing, spraying and other tasks.

There are numerous autonomous and tele-operated vehicle systems described in the literature. Tele-operation has been used for guiding an HST drive vehicle by Murakami et al. (2004). The major challenges encountered in tele-operation are the time delay in communication and the full time attention required of a human. Yekutieli and Pegna (2002) used a sensing arm to sense plants in the path for guidance in a vineyard. However, using an arm would require citrus groves to be even with continuous canopy. There are additional concerns about damaging the tree branches. Ultrasonic sensors have been used for guidance in greenhouses, but they require that the target be perpendicular to the sensor for the ultrasonic waves to be reflected back properly (Subramanian et al., 2004). Dead reckoning is widely

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used in combination with other sensors for autonomous vehicles. Nagasaka et al. (2004) and Kodagoda et al. (2002) have used rotary encoders for detecting vehicle position. However, wheel slip can cause significant error in distance measurements. GPS, in combination with inertial navigation systems, are used in other areas of agricultural vehicle guidance and precision agriculture. Both real-time kinematic (RTK) GPS and differential GPS (DGPS) allow accurate real-time measurement. Nagasaka et al. (2004), Benson et al. (2001) and Noguchi et al. (2002) have found that RTK GPS receivers give very accurate results. Ehsani et al. (2003) evaluated the dynamic accuracy of some low cost GPS receivers with the position information from RTK GPS as reference. They found that these receivers had an average absolute cross-track error around 1 m, when traveling in a straight line. GPS cannot be effectively used for positioning in citrus applications, since the vehicle frequently moves under tree canopy, which blocks the satellite signals to the GPS receiver. Moreover, a system using GPS for guidance requires that a predetermined path be given for the vehicle to follow. Consequently, significant time has to be spent in mapping its path.

Laser radar (ladar) has been used for ranging and obstacle avoidance. Carmer and Peterson (1996) discussed the use of ladar for various applications in robotics. Autonomous vehicle navigation was discussed as a promising application for ladar, due to its ability to accurately measure position. Gordon and Holmes (1988) developed a custom built ladar system to continuously monitor a moving vehicle's position. The testing was done indoors. Ahamed et al. (2004) used a ladar for developing a positioning method using reflectors for infield road navigation. They tested differently shaped reflectors to determine the accuracy in positioning. Ladar has been used for navigating a small vehicle through an orchard (Tsubota et al., 2004). A guidance system using ladar was found to be more stable than using a GPS in a citrus orchard setting. In the research mentioned above, ladar was tested outdoors in the absence of high dust conditions. It is expected that the operation of ladar in dust, fog and similar conditions which block light, would result in reduced performance.

Numerous researchers have applied machine vision to mobile robots. Its low cost and good performance have made it a good candidate for the main guidance sensor. Machine vision and ladar guidance system performance can be comparable (Subramanian et al., 2004). Misao (2001) used machine vision for an automatic steering system on a field sprayer. A video camera was used to acquire the image of the travel path with red targets. Image processing algorithms determined the distance from the current vehicle position to the target, and then the actual position to the desired vehicle path was compared and corrected by automatic steering control. Han et al. (2004) developed a row segmentation algorithm based on *k*-means clustering to segment crop rows. This information was then used to steer a tractor. The guided tractor was able to perform field cultivation in both straight and curved rows. Okamoto et al. (2002) developed an automatic guidance system for a weeding cultivator. A color CCD camera acquired the crop row images, and by processing the images in the computer, determined the offset between the machine and the target crop row. The weeding machine was then steered through the crop row using an electro-hydraulic steering controller.

A good control system is necessary irrespective of the guidance sensor. Feedforward + PID control worked well for guiding a tractor through crop rows (Kodagoda et al., 2002). PID control has been used for guiding a grain harvesting tractor (Benson et al., 2003). In that research, PID was used to calculate the actuator command signal based on the heading offset. The performance of the controller was comparable to that of manual steering. Cho and Ki (1999) used fuzzy logic controller and machine vision for guiding an autonomous sprayer vehicle through orchards. The input information to the fuzzy logic controller was given by both machine vision and ultrasonic sensors.

To date, there has been minimal success in developing commercial autonomous navigation systems for citrus grove applications. However, other similar applications have provided valuable insights for this research. The vehicle used in this research was a John Deere 6410 tractor. Machine vision and laser radar were used as the primary guidance sensors. PID control was selected for controlling the steering of the autonomous vehicle, because it has performed very well in previous mobile robotics research.

2. Objectives

The overall objective is to design guidance systems based on machine vision and ladar that will make the tractor capable of navigating through an alleyway of a citrus grove. Before testing in a citrus grove, it was decided to test the vehicle in a portable path constructed of hay bales. The following specific objectives were selected for this research:

1. Develop electro-hydraulic steering circuit for the vehicle.
2. Develop a mathematical model for the guidance dynamics of the vehicle and design a PID control for steering control.

3. Develop two algorithms for path finding, one using machine vision and the other using laser radar.
4. Test the guidance system's performance on a test track and confirm guidance in a citrus grove.

3. Materials and methods

A John Deere 6410 tractor (Moline, Illinois) was selected for this study. It is well suited for citrus environments and is commonly used in spray applications. The width of the tractor was approximately 2.5 m. To accommodate electronic steering, the tractor was retrofitted with a Sauer Danfoss PVG 32 proportional servo valve (Ames, Iowa). The valve was plumbed in parallel with the existing hydrostatic steering system, as shown in Fig. 1. The valve required an analog voltage signal between 0 and 10 V as input.

A Stegmann incremental rotary encoder (Dayton, Ohio) was mounted on the front steering cylinder for wheel angle feedback. A common 2.4 GHz P4 processor running Windows 2000 operating system was used for processing the vision and ladar algorithms. A "Tern 586 engine" microcontroller (Davis, California) was used for executing real-time control of the servo valve and encoder feedback loop. An amplifier circuit was used to scale the control voltage from the microcontroller to the requirements of the valve. The guidance system architecture is shown in Fig. 2.

The encoder was calibrated by turning the wheels to different angles and recording the number of pulses given by the encoder. Calibration was determined as 7 pulses/° of turn.

Power was taken from the tractor's 12 V dc battery and inverted to 120 V ac for running the PC and the ladar. The 12 V dc tractor supply was used to power the valve and the microcontroller.

The camera used for machine vision was a Sony (NY, USA) FCB-EX780S "block" single CCD analog color video camera with a standard lens and resolution of 640 × 480. A frame-grabber board was used to convert the analog signals to digital images. The ladar used was the SICK LMS 200 (Minneapolis, Minnesota), which has a maximum sweep angle

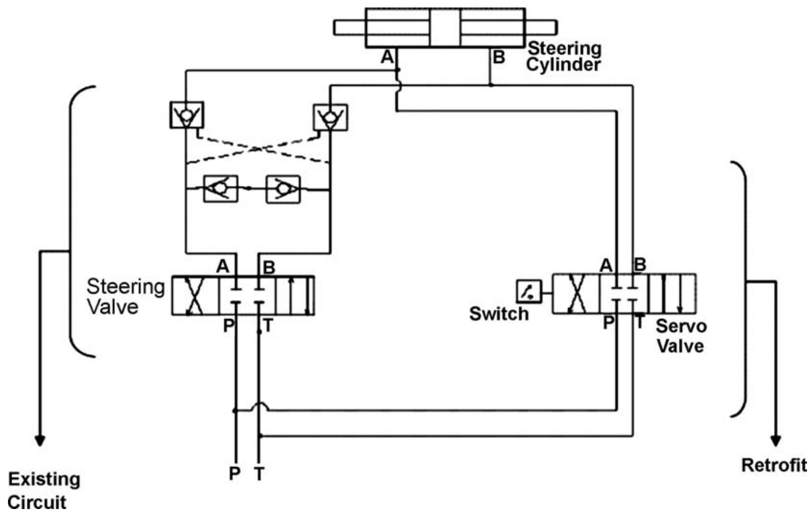

Fig. 1. Electro-hydraulic retrofit of the tractor for automatic guidance.

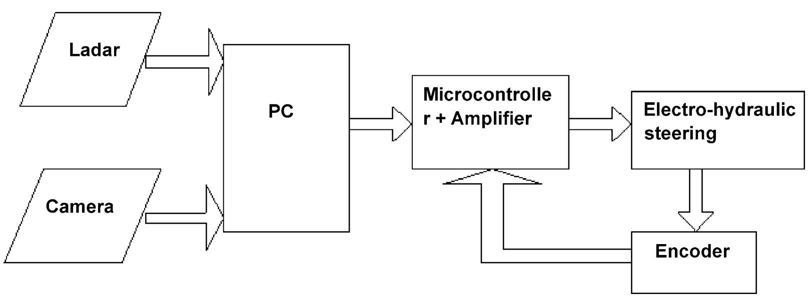

Fig. 2. Guidance system architecture of the vehicle.

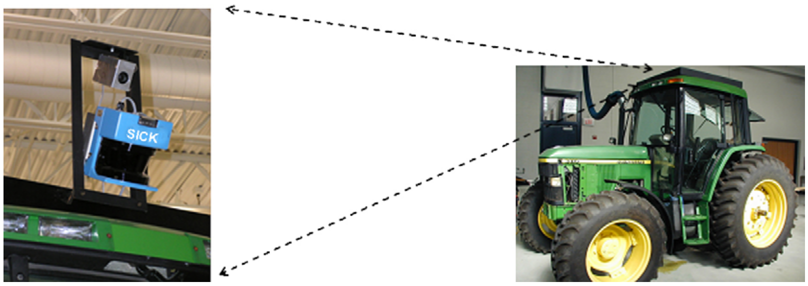

Fig. 3. Camera and ladar mounted on top of the tractor cab.

of 180° and a maximum range of 80 m. RS 232 serial communication at 115,200 baud was used to communicate with the ladar. A Starfire (John Deere, IL,USA) Differential DGPS receiver with 30 cm accuracy was used for determining the vehicle dynamics under open field conditions. The camera, ladar and DGPS receiver were mounted on top of the cab. The camera and the ladar were mounted at a 45° angle looking 1.5 m in front of the tractor as shown in Fig. 3.

For machine vision, color was used as the discriminator for segmenting the path. To account for the varying weather conditions, images were collected over a period of 6 days in 2 months from morning to evening at half an hour intervals. Based on this database of images, a segmentation algorithm was developed as shown in Fig. 4. From the set of images,

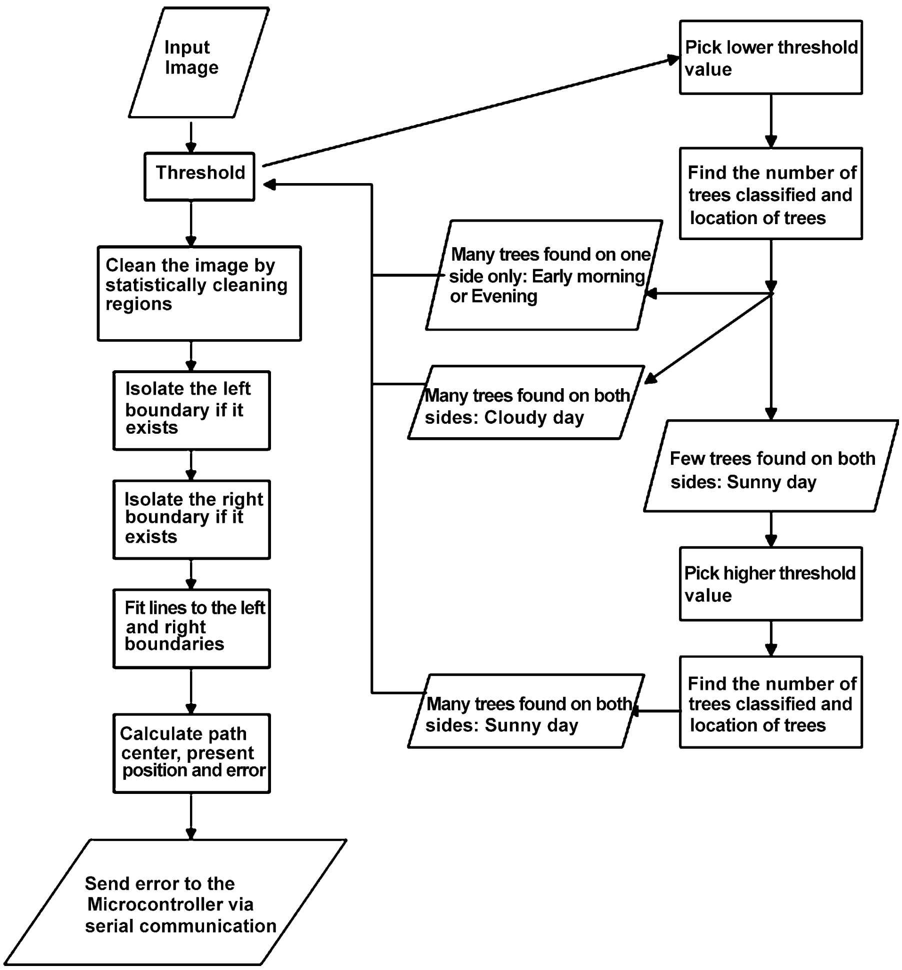

Fig. 4. Machine vision algorithm flowchart.

three types of conditions were observed that require the threshold value to be changed. These are cloudy days when the trees are darker than the path; bright sunny days when the trees are darker than the path but all pixel intensity values are elevated; and early morning and evening, when the sunlight causes the trees on one side of the row to be brighter than the path and the trees on the other side to be darker than the path. Two RGB threshold values were chosen from the image database corresponding to these conditions. To find these RGB threshold values, first, the set of images corresponding to the early morning and evening conditions was taken. The highest of the RGB pixel values in the trees on the side that is darker than the path was chosen as the threshold value. Next, the sunny day condition images were taken and the highest of the RGB pixel values in the trees on both sides of the path was taken as the threshold value. To accommodate these conditions automatically, an adaptive thresholding method was used as shown in Fig. 4.

Next, a series of morphological operations were performed to clearly segment the path and a line was fit for the boundaries, using the least squares method. The error was calculated as the distance from the path center. Camera calibration was done to convert pixel distance to true distance. This was done by marking known distances on the ground in the camera's field of view and the number of pixels corresponding to these distances was counted. To eliminate fluctuation in path tracking due to natural light and camera noise, a time based outlier elimination routine was added to the error calculation. This routine assumes that the error data in a short interval of time of the order of 1 s is normally distributed. When a new error data is found to lie outside two standard deviations of the data from the previous time interval, it is determined as noise and is not used to change the steering for the present time step. If however successive error data are in the same range, then they are taken into account for correcting the steering. An example of grove path estimation using the machine vision algorithm is shown in Fig. 5. Note the path boundary depicted by the superimposed straight lines along the tree boundary. For navigation experiments on the test path, the color threshold for the machine vision algorithm was adopted for detecting hay bales instead of trees.

The laser radar navigation algorithm employed a threshold distance based detection of hay bales. The flowchart of the algorithm is shown in Fig. 6. The plot of the radial distance measured by the ladar for different angles, when driving through the test path, is shown in Fig. 7. The discontinuities in the plot indicate the location of the hay bales. While scanning the field of view using laser radar, if such discontinuities are found in the data, they are marked as hay bales. The path center was determined as the center of the path, between the hay bales on either side.

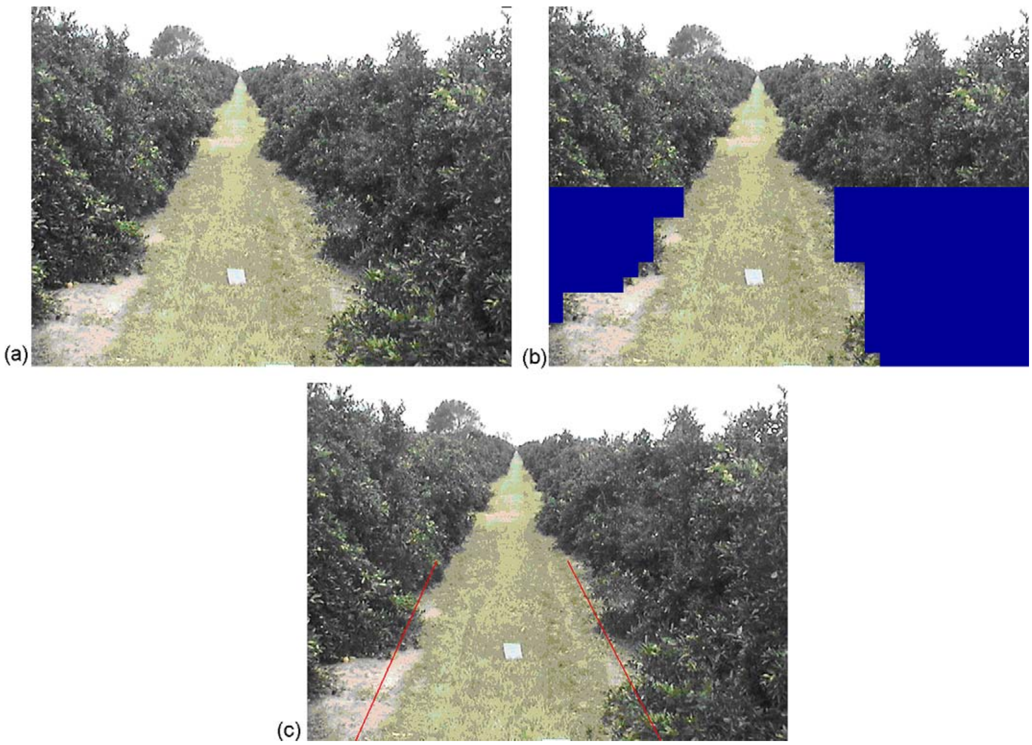

Fig. 5. Machine vision results for citrus grove alleyway: (a) raw image; (b) tree canopy segmentation; (c) path boundary.

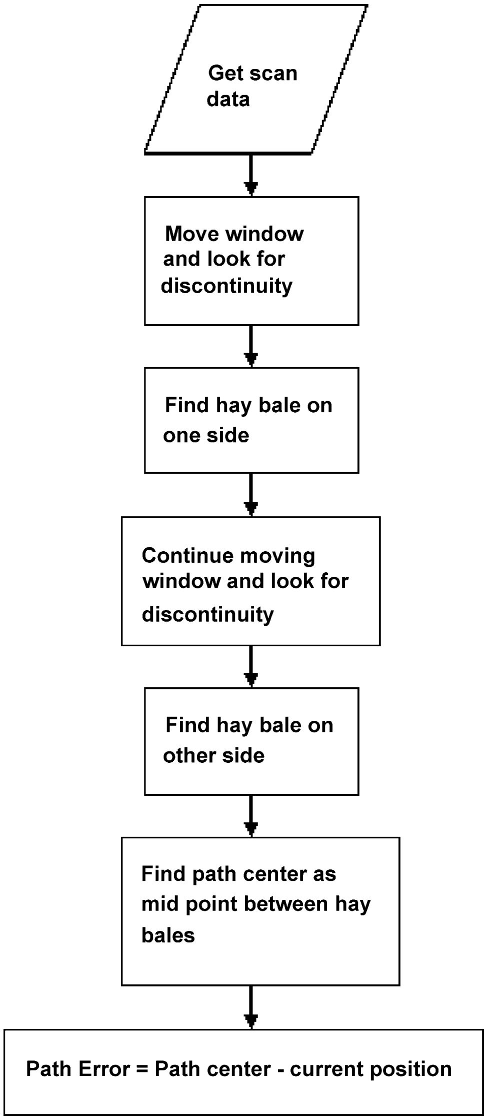

Fig. 6. Ladar algorithm flowchart.

For the determination of the vehicle's guidance dynamics, open loop frequency response tests were conducted in an open field scenario. The tractor engine was set at 2200 rpm and three different speeds of 1.8 m/s (slow), 3.1 m/s (medium) and 4.4 m/s (fast) were set by varying the gears. As the tractor was run, the wheels were automatically turned as a time based sinusoid. The tractor's position was recorded in real-time using the DGPS receiver. The tests were conducted in an open field without any trees or buildings blocking the signal to the DGPS receiver. The receiver communicated with the PC via RS 232 serial communication. The steering turn frequency was performed from 0.07 to 0.3 Hz. Frequencies below 0.07 Hz caused the tractor to veer out of the test area and frequencies above 0.3 Hz were thought to be detrimental to the tractor.

It was observed that the vehicle's position information obtained using the DGPS receiver showed a sinusoidal response at the same frequency as the steering angle. The lateral displacement of the vehicle for a given change in steering angle was recorded as the gain, where the lateral displacement is the displacement of the vehicle in a direction perpendicular to the direction of initial motion. The lateral displacement of the vehicle was calculated from the latitude and longitude data obtained from the DGPS receiver using ArcView 3.3 (ESRI Inc., Redlands, CA). The accuracy of ArcView 3.3 was verified with actual manually measured distance for a few test runs. The gain was plotted against

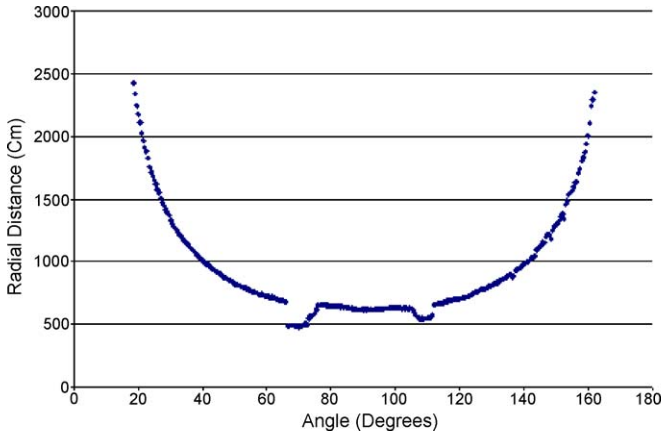

Fig. 7. Radial distance measured by the laser radar in the hay bale path.

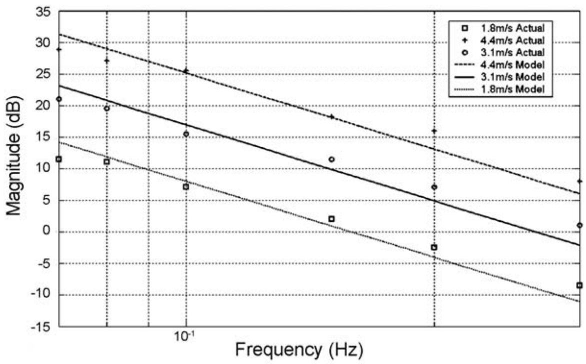

Fig. 8. Open loop theoretical and actual frequency response of the sinusoidal vehicle dynamics test (phase = −180°).

frequency in a bode plot as shown in Fig. 8. The response was observed to be linear. Visually fit lines were used to model this response.

The sinusoidal guidance dynamics data was used to calculate the transfer function between the steering angle and lateral displacement as

$$G(s) = \frac{\text{lateral\_displacement(s)}}{\text{steering\_angle\_change(s)}} = \frac{k}{s^2} \tag{1}$$

The gain k was speed sensitive and was determined as 0.02 (1.8 m/s), 0.07 (3.1 m/s) and 0.13 (4.4 m/s). This model agreed with the model reported by Stombaugh et al. (1999).

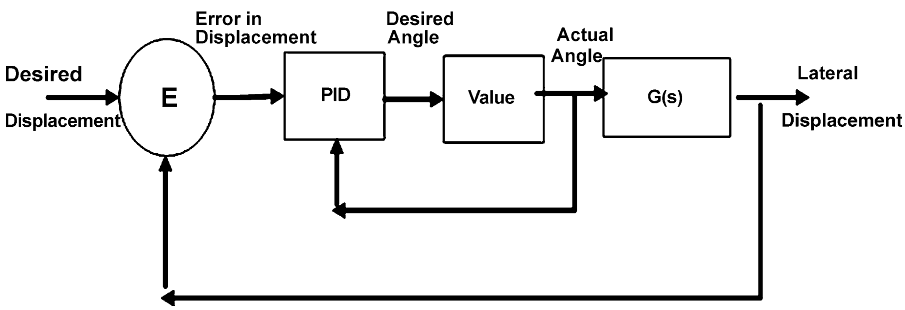

Fig. 9. Simulated vehicle control system block diagram.

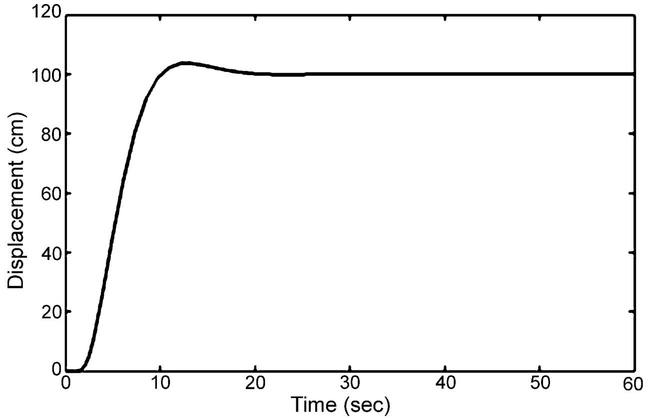

Fig. 10. Simulated 1 m step response of the vehicle at 3.3 m/s.

Based on the determined theoretical model, a PID control system was designed (Fig. 9). The PID gains were tuned by simulation in Simulink, using the Ziegler Nichols method of tuning for a closed loop system. Tuning was optimized for zero steady state error and low overshoot. Fig. 10 shows the 1 m step response when simulated for the 3.3 m/s speed.

4. Experimental procedure

Typical citrus grove alleyways are practically straight rows. It was felt that testing the vehicle in straight and curved paths at different speeds would be a more rigorous test of the guidance system's performance than testing in straight grove alleyways. For this purpose, a flexible wall track was constructed using hay bales to form a test path. The hay bales provide a physically measurable barrier, which aids in operating the ladar guidance system and color contrast with grass which is useful for vision-based guidance. In addition, when testing a large tractor, minor losses would occur if the tractor runs over a barrier of hay bales. The control algorithms used with machine vision or ladar-based guidance are practically identical for either test track. The only modification in the vision algorithm was the threshold value for image segmentation. These threshold values were determined for both paths using techniques described earlier. The PID controller and the encoder performance are independent of the physical environment around the vehicle. The hay bale width was 45 cm and the boundary height was 90 cm after stacking hay bales two deep. Two types of path were used, a straight path and a curved path. The length of the straight path was 22 m. A 10 m extension was added to the straight path to form the curved path. The radius of curvature was 17 m at the curve. The path width was 3.5 m throughout the length. The paths used in this study to evaluate the guidance system performance are shown in Fig. 11(a) and (b).

Experiments were conducted to check the robustness and accuracy of the vision and laser radar guidance systems in navigating the different test paths at different speeds. Experiments were conducted for three different speeds, 1.8, 3.1 and 4.4 m/s. These speeds corresponded to the perceived slow, medium and fast speeds for a tractor operating in a grove. The speeds were measured using an ultrasonic ground speed sensor.

Fig. 11. Guidance system test path: (a) straight and (b) curved.

Fig. 12. Vehicle in the citrus grove alleyway.

The vehicle was manually driven to the starting position, resulting in different initial offset and heading angles for each repetition. Once positioned, the vehicle was started under autonomous control and allowed to navigate down the path. Three repetitions were performed for each experiment. A rotating blade was attached to the draw bar, which marked a line on the ground as the vehicle moved. This line represented the path center traveled by the tractor. The errors were manually measured after each run using the distance from the marked line to the hay bale boundary. The error measurements were accurate to 0.1 cm. The measurements were taken at regular intervals of 30 cm. Due to the unpredictable nature of the starting and ending data, the first 5% and last 5% of the data record was discarded for statistical analysis. However, the plots show the full data record, which illustrates the random nature of the vehicle starting position.

Data points were taken from each run as described above in order to calculate the path root mean square error, standard deviation, maximum error and average error. The rms error equation is shown in Eq. (2):

$$\text{rms error} = \sqrt{\sum_{i=1}^{N} \frac{e_i^2}{N}} \tag{2}$$

where e_i is the path error and N is the total number of data points. These measures were used to compare the performance of the two guidance sensors, the two different path configurations and the three speeds.

After achieving satisfactory performance in the test path, trials were conducted in an alleyway of the citrus grove. For initial grove trials, only machine vision was used due to machine vision easily adapting to grove conditions. Ladar, on the other hand, requires that additional data filters be designed to compensate for noise due to random orientation of the tree leaves. Future development is planned to test ladar in the grove. The machine vision guidance system was used to guide the tractor through an alleyway of a citrus grove on the University of Florida campus as shown in Fig. 12. The average path width was 4.6 m. The tractor was driven to the grove and started in the automatic mode at the beginning

Table 1
Performance measures of the vehicle's guidance system obtained from the experiments conducted in the straight test path

Sensor	Speed (m/s)	Average error (cm)	Maximum error (cm)	Standard deviation (cm)	rms error (cm)
Vision	1.8	2	3.9	0.8	2.2
	3.1	2.8	5.9	1.2	3.1
	4.4	2.8	6.1	1.5	3.2
Ladar	1.8	1.6	3.3	0.7	1.8
	3.1	1.6	3.9	0.8	1.8
	4.4	3.1	6.1	1.6	3.5

Table 2
Performance measures of the vehicle's guidance system obtained from the experiments conducted in the curved test path at 3.1 m/s

Sensor	Path	Average error (cm)	Maximum error (cm)	Standard deviation (cm)	rms error (cm)
Vision	Straight section (22 m)	2.8	5.1	1.2	3.1
	Curved section (10 m)	2.7	3.9	0.4	2.7
	Overall (32 m)	2.8	5.1	0.9	2.9
Ladar	Straight section (22 m)	1.6	3.9	0.8	1.8
	Curved section (10 m)	4.1	6.1	2.9	4.9
	Overall (32 m)	2.5	6.1	1.6	2.9

of an alleyway. The guidance system was allowed to guide the tractor through the entire length of the alleyway. The performance was visually observed.

5. Results and discussion

Tests were conducted on each of the sensor and track conditions to observe the behavior of the vehicle under various speeds. During each trial run, the path position and error were recorded manually using a tape measure. The rms error,

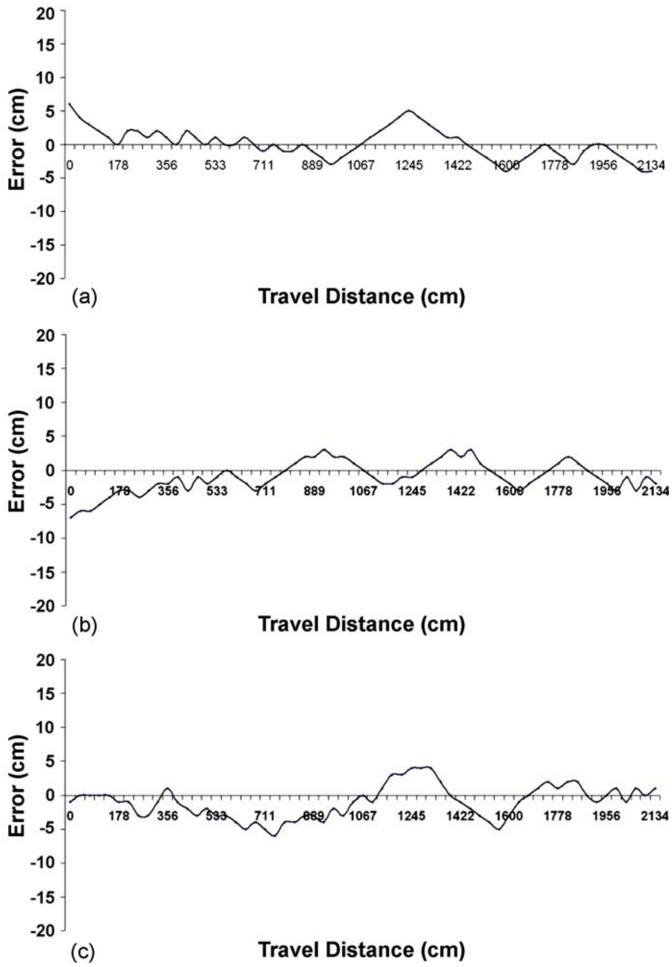

Fig. 13. Performance of the machine vision guidance in the straight path: (a) 1.8 m/s; (b) 3.1 m/s; (c) 4.4 m/s.

average error, standard deviation of the error and the maximum error were calculated for each experiment, by averaging the data over the three repetitions of each condition. The results were then compared for the different conditions. The path error, which is the deviation from the centerline of the aisle way, was plotted over the length of the test path for the different conditions. Path errors were adjusted for local variation in hay bales. The performance measures are shown in Table 1 for straight path and Table 2 for curved path. It should be noted that Table 2 data is broken down to the straight, curved and overall path errors.

Fig. 13 shows the performance of the machine vision guidance system at the three different test speeds. The average error was less than 3 cm for all speeds as noted in Table 1. The performance was better at 1.8 m/s than at the two higher speeds. As shown in Fig. 13, the PID control is attempting to drive the error to zero. The rms error is 3.2 cm at the fastest speed and demonstrates a good control performance visually similar to human driving. The machine vision guidance performed well in the straight path. The performance was better at lower speeds.

Fig. 14 shows the performance of the laser radar guidance system at the three different speeds. Once again the PID control is driving the error around zero. The average error at the lowest speed (1.6 cm) is almost half the error at the highest speed (3.1 cm). Laser radar is a more accurate measuring device than machine vision resulting in lower tracking errors, at the two lower speeds. However the ladar error is 10.7% higher at 3.1 cm when traveling at 4.4 m/s. The machine vision algorithm was run at 20 Hz, whereas the laser radar refresh rate was only 6 Hz at half degree resolution when using a standard serial port communicating at 115,200 baud. The slower ladar refresh rate means that, less current data is available for the laser radar guidance system than the machine vision

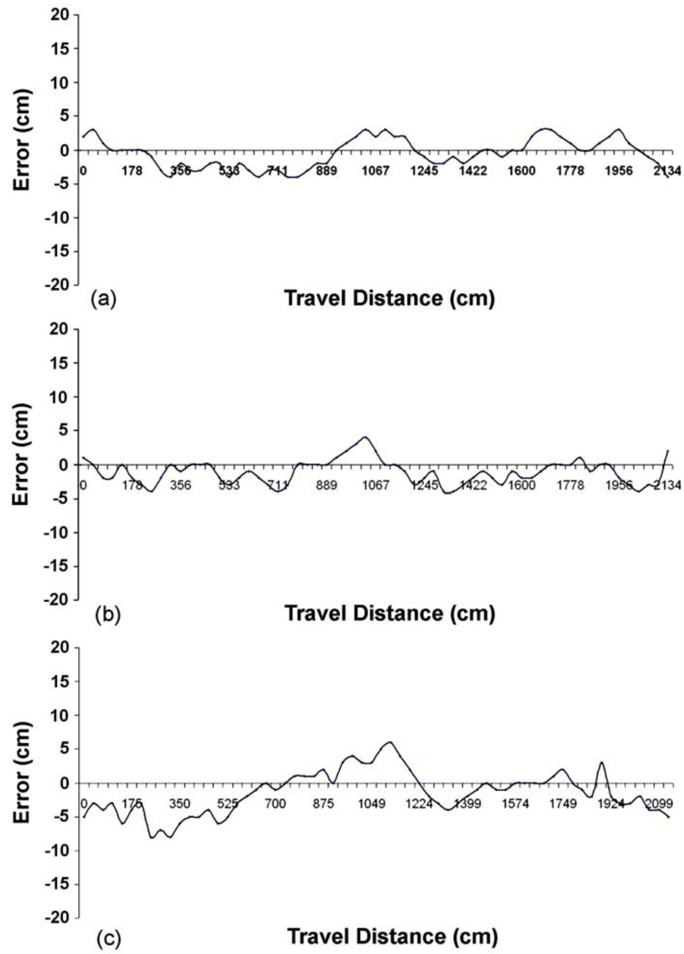

Fig. 14. Performance of the laser radar guidance in the straight path: (a) 1.8 m/s; (b) 3.1 m/s; (c) 4.4 m/s.

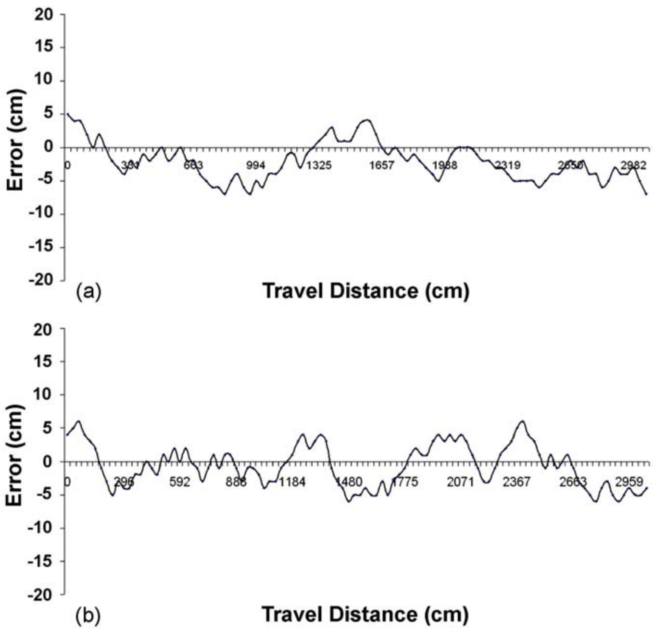

Fig. 15. Performance in the curved path at 3.1 m/s: (a) machine vision guidance and (b) laser radar guidance.

guidance system, in a given time interval. At high speeds of 4.4 m/s, this factor reduces the performance of the laser radar guidance system, whereas the machine vision guidance system is not severely affected. By using a high speed serial communication card (500 kbaud), the laser radar refresh rate can be increased and therefore its performance at speeds 4.4 m/s and higher, can be improved. None the less, the rms error was only 3.5 cm at the fastest speed.

Fig. 15 shows the performance of the vision and laser radar guidance systems at a speed of 3.1 m/s in the curved path. The performance of the two systems was visually as good as a human driving the tractor. The vision guidance had an average error over the entire track of 2.8 cm whereas the laser radar guidance system had an average error of 2.5 cm as shown in Table 2. The maximum error, rms error and standard deviation of machine vision-based guidance, when run at 3.1 m/s in curved path seems to have done better than in the straight path. It is to be noted that the curved path consists of a straight section followed by a curved section. The camera's wide field of view is smaller than that of the ladar and therefore when the vehicle gets to the curved section, only one side of the path boundary is visible in the field of view. The machine vision tries to guides the vehicle at a constant distance from the visible boundary. This can be observed in Fig. 15a (vision in curved path at 3.1 m/s). Since the curve starts at some where around 2100 cm travel distance, Fig. 15a shows that the vision-based PID control does not attempt to drive the error to the center of the path once the tractor enters the curve. However, the ladar-based PID control in Fig. 15b does continue to cross the zero error path center in the curve section. The maximum error, rms error and standard deviation of error in this curved section are lower than that for the straight section. When averaged over the entire path, the error parameters appear lower for the curved path than for the straight path. The laser radar guidance system's overall accuracy was slightly more accurate than the vision guidance when considering average error. As before, it performed better in the straight path section of the path, but was less accurate in the curve than the vision system. It also seems to exhibit larger swings about zero error than the vision system as evident by the larger maximum error. This may be due to some natural dampening that occurs in the less accurate vision measurement algorithm. This can be attributed to the fact that the laser radar is more accurate at detecting the path center than the vision guidance.

The good performance in the hay bale track encouraged trials in the citrus grove alleyway. The guidance system successfully guided the tractor through the alleyway. Initial trials using machine vision for guidance showed a lot of promise. The machine vision algorithm clearly segmented the path to be traversed. However, the non-uniformity of

the canopy surface caused the controller to over compensate for the undulation in canopy surface resulting in a more zigzag transit of the alleyway. Control enhancements are planned to further improve the guidance system performance in the grove.

6. Conclusion

Machine vision and laser radar based guidance systems were developed to navigate a tractor through the alleyway of a citrus grove. A PID controller was developed and tested to control the tractor using the information from the machine vision system and laser radar. A flexible curvature track was built using hay bales as boundaries and the vehicle was tested under straight path and curved path configurations. Tests were conducted at three different speeds of 1.8, 3.1 and 4.4 m/s. Path tracking comparisons were made between the vision-based control and a ladar-based control. The traversed path was marked on the ground and measured manually.

Error comparisons were made using rms error and mean instantaneous error. It was found that the ladar-based guidance was the better guidance sensor for straight and curved paths at speeds of up to 3.1 m/s. Communication speed between the laser radar and the computer was a limiting factor for higher speeds. This problem can be solved by a faster communication speed using a high speed serial communication card in the PC. This card was not available during this research. Machine vision-based guidance showed acceptable performance at all speeds and conditions. The average errors were below 3 cm in most cases. The maximum error was not more than 6 cm in any test run. These experiments demonstrated the accuracy of the guidance system under test path conditions and successful guidance of the tractor in a citrus grove alleyway. However, additional testing is needed to improve the performance in the citrus grove. It was proposed that a control scheme, which used both machine vision and laser radar, may provide a more robust guidance, as well as provide obstacle detection capability.

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